

# Coping with area price risk in electricity markets: Forecasting Contracts for Difference in the Nordic power market

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## Abstract

Contracts for Difference (CfDs) are forwards on the spread between an area price and the system price. Together with the system price forwards, these products are used to hedge the area price risk in the Nordic electricity market. The CfDs are typically available for the next two months, three quarters and three years. This is fine, except that CfDs are not traded at NASDAQ OMX Commodities for every Nord Pool Spot price area. We therefore ask the hypothetical question: What would the CfD market price have been, say in the price area NO2, if it had been traded? We build regression models for each observable price area, and use Bayesian elicitation techniques to obtain prior information on how similar the different price areas are to forecast the price in an area where CfDs are not traded.

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# 1 Introduction

The Nordic electricity spot power market (Nord Pool Spot) is divided into several price areas (Kristiansen, 2004a; Weron, 2006; Benth et al., 2008), with the system price being a common reference price. The different price areas result from capacity constraints. In theory, if an overall market balance can be achieved without a need to utilise all available capacity between neighbouring areas, the prices are equal in all areas.

There is a parallel financial market, NASDAQ OMX Commodities, where players in the market can hedge their positions through futures (days, weeks) and forwards (months, quarters and years) against the system price. However, nobody is exposed to the system spot price, but rather to the area spot price. Therefore, the participants can in addition buy CfDs (Contracts for Difference) in order to hedge the remaining difference between the system and price area risk. The CfDs are typically available for the next two months, three quarters and three years. This is fine, except that CfDs are not traded at NASDAQ OMX Commodities for every Nord Pool Spot price area. There is still a need for hedging in those price areas where CfDs are not traded at the exchange, but this is rather done through OTC (over-the-counter) trades. The price area risk is large, which is exemplified by the spot price in the NO1 (Oslo) area. The NO1 spot price was quite close to the system spot price until 2007. During 2007, the NO1 price fell below 20% of the system price. The price areas are defined by the transmission system operators (TSOs). In Norway, the TSO Statnett has redefined the price areas five times between 2006 and 2011, making the historic data not

directly applicable for new price areas. We therefore ask the hypothetical question: What would the CfD market price have been, say in today's NO2, if it had been traded?

There are several reasons for being interested in this hypothetical price. First and maybe foremost, we can then assess the marking-to-market value of possible CfDs entered OTC (over the counter) for the non-traded areas. Second, we could possibly derive portfolios of the traded CfDs to mimic a CfD in the non-traded areas. Third, CfD prices can be used for internal risk and prognosis considerations. Note that we seek to find the non-traded CfD prices, which is fair in terms of the way the market operates, but may include (the non-observable) risk premiums. We will embroider this alternative approach in the Discussion.

This topic has not been discussed in the scientific literature, but Nord Pool Spot system prices have been studied quite extensively (Benth et al., 2008; Erlwein et al., 2010; Botterud et al., 2010). There has been less focus on Nord Pool Spot area prices, with some noteworthy exceptions (Kristiansen, 2004a; Fridolfsson and Tangerås, 2009; Løland and Dimakos, 2010). Previous work on Nordic CfD prices includes Kristiansen (2004b), who investigated hedging through these CfDs. He found that the contracts appear to be overpriced, but the results are preliminary due to a relatively new CfD market. Marckhoff and Wimschulte (2009) found a significant relation between the spreads (Nord Pool Spot system minus area prices) and relative water reservoir levels for all areas except NO2 (Trondheim at the time) on more recent data (2001–2006). CfDs are found to have significant risk premiums, with different signs and magnitudes between areas.

Our aim is to build a model for the expected CfD price even for almost brand new price areas where CfD products are not traded. We start by fitting standard regression models for the observed CfDs for each price area and each CfD product. If the regression model and its parameters had been the same for each observed price area, we could have validated it properly and used it for every unobserved area as well with local covariate values. Alas, the price areas are too different for this to work. Alternatively, we could have found the unobserved CfD prices as (model) averages of the observed ones, but the averaging weights can not be found from the data at hand. Another approach would be to estimate price area specific risk premiums in the spirit of Marckhoff and Wimschulte (2009). Since the risk premiums are not directly observable and we are interested in the CfD prices, which are functions of price expectations and risk premiums, modelling risk premiums would be a detour here. We are therefore left with the fitted regression models for each observed price area and the covariates for the unobserved ones. The only viable path out of this deadlock is the use of Bayesian methods.

We view this as a statistical elicitation problem (O'Hagan et al., 2006). Our method requires that we (or industry experts) specify how much the (unobserved) price in area X resembles the (observed) price area Y regarding covariate 1, 2, and so on. Therefore, the covariates have to be relatively few, readily interpretable and describe the observed CfD prices well. To assess the corresponding uncertainty, we ask how many months of data this opinion corresponds to.

The problem at hand almost has no solution, but it still deserves our

best efforts. Proper validation is impossible, and we must simply rely on our modelling approach. Yet, we can show that our method provides sensible forecast results. Corresponding forecast problems with a missing response in some data cells and subjective information can benefit from our approach.

We proceed with presenting the data (Section 2), and outline our approach in detail (Section 3). The method is demonstrated (Section 4), followed by a discussion of our approach (Section 5).

## 2 Data

We use data from January 1st 2006 until January 31st 2011. During this period, Statnett has redefined the Norwegian price areas five times (marked by dashed vertical lines in Figures 3–6), while the Finnish (FI, one price area), Danish (DK1 and DK2, corresponding to western and eastern Denmark, respectively) and Swedish (SE) price area definitions have not changed. Svenska Kraftnät, the Swedish TSO, has from the 1st of November 2011 divided Sweden into four areas, and Norway is presently divided into five areas (NO1–NO5, Figure 1).

We use the following data and nomenclature:  $CfD_{tah}$ : CfD price for day  $t$ , area  $a$ , horizon  $h$ ,  $FW_{th}$ : Forward price for day  $t$ , horizon  $h$ ,  $SA_{ta}$ : Area spot price for day  $t$ , area  $a$ ,  $SS_t$ : System spot price for day  $t$  and  $WA_{ta}$ : Reservoir level (seasonally adjusted, see below) for day  $t$ , area  $a$ . Day  $t = 1.1.2006, 2.1.2006, \dots, 31.1.2011$ . The price areas  $a$  include FI, DK1, DK2, SE, NO1–NO5. Figure 2 shows the area and system spot prices.

The horizon can be 1-2 months, 1-3 quarters or 1-3 years, which we write

as  $h \in \{M1, M2, Q1, Q2, Q3, Y1, Y2, Y3\}$ . Area spot prices are available for all areas, while CfDs are available for all areas except NO2–NO5. The CfD and forward data are not strictly daily: First, CfDs and forwards are only sold on working days. Second, and most important, CfDs for a particular area are not actually sold each working day, even though a CfD price is recorded – i.e., if no CfD is sold on a working day  $t$ , the recorded price is just the price at the most recent  $t' < t$  when a CfD was sold. Thus, if we observe equal CfD prices for two subsequent days, it may be either because 1) a CfD were actually sold at the same price both days or 2) no CfD was sold on the second day. Unfortunately, we do not have data on sales volume, but it is known that volumes can be rather low. It is, however, easy to incorporate volumes as weights in our model. We do not suspect that the general picture would be very different with the inclusion of volumes.

We may define the *area a specific forward price* by

$$FW_{th} + \text{CfD}_{tah}. \quad (1)$$

Since the area specific forward price must be positive,  $\text{CfD}_{tah} \in (-FW_{th}, \infty)$ , and we proceed with modelling  $\text{CfD}_{tah}$  on the original scale.

The covariates are chosen because they in theory should have predictive power and because they are readily interpretable. Kristiansen (2004b) formulated a risk premium model for the CfDs where the CfD is the discounted, expected difference between the future area spot price and the future system spot price. In a market without flexibility, storage capacity (like gas storage or water reservoirs) and risk neutral players, the current difference between

the area and system spot price should be a good forecast for the future CfD price. To relax this assumption somewhat, we include both the area and the system spot price as covariates instead of the difference between them.

The CfD price can be seen as an absolute or relative deviation from the system forward price (1). If the deviation is relative, the forward price level should be of importance for the CfD, and we therefore include the corresponding forward price (with the same delivery period as for the CfD) as a covariate.

It is reasonable to assume that the volatility will increase for products that are close to maturity (Aas and K  resen, 2004). Time to maturity was included as a covariate in a preliminary analysis, but turned out to be non-significant. We believe the reason is that conceivable time to maturity effects are included in  $FW_{th}$ .

Since Marckhoff and Wimschulte (2009) found a significant relation between the empirical spreads and relative water reservoir levels for most price areas, we include the reservoir level  $WA_{ta}$  as well for the price areas with hydro power (Sweden, Finland and all Norwegian ones, see Figure 3). The series were seasonally adjusted by subtracting seasonal terms

$$\lambda_{ta} = \gamma_a^{(0)} + \sum_{j=1}^2 \gamma_{a,j}^{(1)} \sin\left(\frac{2\pi jt}{52}\right) + \gamma_{a,j}^{(2)} \cos\left(\frac{2\pi jt}{52}\right),$$

which were estimated by least squares regression on logit-transformed variables (to transform from  $(0, 100\%) \rightarrow \mathbb{R}$ ). This was done in order to have variables that represent deviations from a normal water reservoir level. The  $\lambda_{ta}$  term was estimated with data from 2006 to 2011 for every historical price

area, and the corresponding residuals for the applicable price area definition were used.

### 3 Methods

Consider a specific horizon, for example one quarter ahead. Then, for each price area, we assume the linear regression model

$$\text{CfD}_{ta} = \beta_{\text{FW}}^{(a)} \text{FW}_t + \beta_{\text{SA}}^{(a)} \text{SA}_{ta} + \beta_{\text{SS}}^{(a)} \text{SS}_t + \beta_{\text{WA}}^{(a)} \text{WA}_{ta} + \varepsilon_{ta}. \quad (2)$$

Note that there is no intercept term in the above model. This is for two reasons: First, due to the nature of the CfD as the difference of a hypothetical “area-specific forward price” and the actual system forward price, it is reasonable to assume that the expected CfD should be zero if all the covariates in (2) are zero. Second, it is not clear how one could elicit intercept terms for areas without observed CfD. There are obviously common features between the horizons, but the effect of each covariate is slightly different for each horizon. In addition, there is plenty of data for each horizon, so some sort of shrinking between horizons to reduce the number of parameters is not necessary. We therefore consider each horizon separately.

For areas  $a \in \{\text{DK1}, \text{DK2}, \text{FI}, \text{NO1}, \text{SE}\}$  we observe both  $\text{CfD}_{ta}$  and the explanatory variables, so we could fit the linear model using ordinary least squares. However, for the areas  $a \in \{\text{NO2}, \text{NO3}, \text{NO4}, \text{NO5}\}$  we only observe the explanatory variables. Therefore, we obviously cannot fit the linear model for these areas. To avoid this problem, it might seem



natural to let the regression coefficients for each explanatory variable be equal over areas, so that we effectively have one large model over all areas. Unfortunately, this model fits the observed areas very poorly. Using separate linear models for each area fits the observed data quite well.

Because of all this missing information, we find it most sensible to use some type of elicitation approach in order to take advantage of domain experts' prior knowledge of how the areas differ. A relatively simple way of doing this is to keep the linear model (2) for the “with-CfD” areas, while assuming that the regression coefficients for the “without-CfD” areas are given as a weighted average of the coefficients for the “with-CfD” areas. The weights are provided by the domain expert, together with an assessment of how confident the expert is in the accuracy of the weights.

In more compact vector form, we may write this model as

$$\mathbf{CfD}_a = \mathbf{X}_a \boldsymbol{\beta}_a + \boldsymbol{\varepsilon}_a,$$

where  $\mathbf{CfD}_a$  denotes the vector of CfDs at all time points for area  $a$ ,  $\mathbf{X}_a$  is the matrix of covariates,  $\boldsymbol{\beta}_a$  the vector of regression coefficients, and  $\boldsymbol{\varepsilon}_a$  is a vector of noise terms. From now on, for ease of notation, we number the areas, and order them such that  $a = 1, \dots, q$  are the “with-CfD” areas, while  $a = q + 1, q + 2, \dots, m$  are the “without-CfD” areas.

We further assume that

$$\mathbf{CfD}_a | \boldsymbol{\beta}_a, \sigma_a^2, \mathbf{X}_a \sim N(\mathbf{X}_a \boldsymbol{\beta}_a, \sigma_a^2 I)$$

with a uniform prior on  $(\boldsymbol{\beta}_a, \log \sigma_a)$ , i.e.

$$p(\boldsymbol{\beta}_a, \sigma_a^2 | \mathbf{X}_a) \propto \sigma_a^{-2} \quad (3)$$

(which is a standard non-informative prior for linear regression).

For the unobserved areas  $a > q$  we also assume that

$$\mathbf{CfD}_a | \boldsymbol{\beta}_a, \sigma_a^2, \mathbf{X}_a \sim N(\mathbf{X}_a \boldsymbol{\beta}_a, \sigma_a^2 I),$$

but here we cannot estimate the regression parameters directly, since we do not have any observed CfD. We assume that each regression parameter for the unobserved areas  $a > q$  is a weighted average of the regression coefficients for the observed areas, so that

$$\beta_{ia} = \sum_{j=1}^q w_{ij} \beta_{ij}, \quad a > q,$$

where  $\sum_{j=1}^q w_{ij} = 1$  for each  $i = 1, \dots, p$ . Further, we assume that each vector  $\mathbf{w}_j = (w_{1j}, \dots, w_{qj})$  is Dirichlet distributed:

$$\mathbf{w}_j \sim \text{Dirichlet}(\rho_{1j}, \dots, \rho_{qj}, n).$$

The Dirichlet distribution was chosen because it gives a simple, interpretable way (described below) for the expert to quantify her level of certainty in her prior judgments. Also, viable alternatives to the Dirichlet prior seems to be lacking in this case (O'Hagan et al., 2006, Section 6.5)

The parameters  $\rho_{1j}, \dots, \rho_{qj}$  and  $n$  are determined subjectively, using a

structured (guided) elicitation procedure. Each  $\rho_{ij}$  may be interpreted as a measure of how much the effect of covariate  $j$  on the CfD price in area  $a$  resembles the effect of covariate  $j$  on area  $i$ , relative to the other observed areas. While this certainly sounds quite technical when expressed in such general terms, it still remains amenable to elicitation. For example, we may pose the question to an expert in the following way: “Consider the effect of hydrological balance (in NO2) on (the hypothetical) CfD price in area NO2. How similar is this to the effect of the hydrological balance (in NO1) on the (observed) CfD price in NO1?” By repeating this question for each observed area, and scaling the answers so that they sum to one, we obtain the parameters  $\rho_{ij}$  for area NO2. We also want an assessment of the level of certainty the expert is willing to attach to her judgments. This is provided by the parameter  $n$ , which may be elicited by the following question: “Consider your answer to the previous question. This is a question which also could have been answered using empirical data, if these were available. How many months of data do you feel would give an information content equivalent to your subjective assessment?”.

Suppose you are determining the vectors  $\mathbf{w}_j$  for NO2. The simplest solution is to say that it will react to the covariates as in NO1. If you believe that the CfD price should react quicker to the spot price signal, more weight could be put on the area and system spot price ( $SA_{ta}$  and  $SS_t$ ) for the Danish areas DK1 and DK2. Naturally, Danish hydro power is very limited, so the corresponding reservoir content regression coefficients are set to zero. An example of specified values for the parameters  $\rho_{1j}, \dots, \rho_{qj}$  for NO2 is given in Table 1.

<b>NO2</b>	DK1	DK2	FI	NO1	SE	Months of data
<i>FW</i>	5%	5%	5%	75%	10%	1
<i>SA</i>	5%	5%	5%	80%	5%	1
<i>SS</i>	5%	5%	5%	80%	5%	1
<i>HY</i>	0%	0%	5%	85%	10%	1

Table 1: Specified prior distribution for the parameters in the Dirichlet distribution for NO2.

Most weight is put on the NO1 area, since we expect it to resemble NO2 the most. Except for the missing Danish water reservoirs, all parameters are set to at least 5%, since we are quite uncertain. For the same reason, we feel that one month of data would give informational content equivalent to our subjective assessment. We have experimented with different prior weights, and moderate changes does not affect the results too much.

After finishing the elicitation, the full model is fitted using the following Monte Carlo algorithm:

1. For each observed (“with-CfD”) area  $i = 1, \dots, q$  and each covariate  $j = 1, \dots, p$ :
  - (a) Draw  $p_{ij}$  from the Dirichlet distribution with parameters  $\rho_{ij}$  and  $n$ .
  - (b) Draw regression parameters  $\beta_{ij}$  from the posteriors of the linear model parameters for the observed areas (we used the function `sim` in the R package `arm` (Gelman et al., 2012), see also Section 7.2 of Gelman and Hill (2006)).
2. For each unobserved (“without-CfD”) area  $i = q + 1, \dots, m$  and each covariate  $j = 1, \dots, p$ , calculate the predicted mean CfD  $\mu_{it} = \sum_{j=1}^p \tilde{\beta}_{ij} x_{ijt}$ ,

where  $\tilde{\beta}_{ij} = \sum_{k=1}^q p_{kj} \beta_{kj}$ .

Repeating steps 1 and 2 above  $N$  times then provides  $N$  samples of the predicted mean CfD  $\mu_{it}$ , which can be used for probabilistic forecasting, for example using quantiles or the mean of the sampled  $\mu_{it}$ .

## 4 Results

Figures 4–6 show predicted, daily CfD prices for horizons M1, Q1, and Y1, respectively, with a 95% prediction interval shown in grey, together with the observed NO1 and SE prices for comparison. For the M1 horizon, the predicted CfD prices for NO2 and NO3 are quite similar, but there are some differences: For example, the NO3 price has a sudden spike in the beginning of 2010, which is not seen for NO2. Both NO2 and NO3 seem quite similar to SE. The NO4 and NO5 areas have only a rather short history, so it is not clear whether they are more similar to NO1 or SE. For NO2 and NO3, we see that the uncertainty varies a great deal between area definition periods — shorter periods have a larger uncertainty, since the amount of available data is smaller. For the Q1 horizon, results look similar. Finally, for the Y1 horizon, it is less clear whether the NO2 and NO3 prices are more similar to NO1 or SE, but they might still seem slightly more like SE. The uncertainty is quite large at times, particularly for NO2 in 2006. Estimated regression coefficients from the linear regression model in Equation (2) is shown in Table 2.

As explained in Section 2, for a given area, the sum of the CfD and the corresponding system forward price may be interpreted as an area-level

<b>M1</b>	DK1	DK2	FI	NO1	SE
$\beta_{SA}$	0.623	0.523	0.481	0.521	0.515
$\beta_{SS}$	-0.151	-0.050	-0.439	-0.449	-0.460
$\beta_{FW}$	-0.325	-0.304	-0.003	-0.097	-0.008
$\beta_{WA}$	NA	NA	1.200	1.061	-0.885
<b>Q1</b>	DK1	DK2	FI	NO1	SE
$\beta_{SA}$	0.504	0.342	0.288	0.363	0.373
$\beta_{SS}$	-0.163	-0.152	-0.189	-0.390	-0.227
$\beta_{FW}$	-0.174	-0.002	-0.062	-0.005	-0.102
$\beta_{WA}$	NA	NA	2.216	0.906	0.723
<b>Y1</b>	DK1	DK2	FI	NO1	SE
$\beta_{SA}$	0.076	0.114	0.059	0.029	0.023
$\beta_{SS}$	0.038	0.021	-0.020	-0.065	-0.004
$\beta_{FW}$	0.032	0.036	-0.010	0.027	0.006
$\beta_{WA}$	NA	NA	0.565	-0.743	-0.844

Table 2: Estimated regression coefficients (rounded to three decimal places) from the linear regression model in Equation (2) for horizons M1, Q1, and Y1. Danish areas DK1 and DK2 have no regression coefficient for the reservoir level; since there is no hydropower production in Denmark, the reservoir level is left out from the linear model for the Danish areas.

forward price. Therefore, in the absence of risk premia, each CfD + FW sum should be similar to the realised area spot price, averaged over the contract period of the CfD. Figures 7-9 show a comparison of observed (NO1, DK1, DK2, FI, SE) and predicted (NO2–NO5) CfD + FW and the realised averaged area spot price, for all price areas, and for horizons M1, Q1 and Y1. Clearly, the correspondence is quite good between the observed and predicted CfDs, even for the longer-term horizons Q1 and Y1. For Y1, we only have a few years of observed data, and there is considerable uncertainty on how well the model performs for the longest horizons.

## 5 Discussion

We have asked and answered the hypothetical question: What would the CfD market price have been, say in NO<sub>2</sub>, if it had been traded? We will not know for certain, but we have presented a statistical approach to this class of problems, which works almost without data. The approach can be especially useful in markets where the price areas definitions change over time, as they have done in the Nordic power market. Our method can be applied in OTC trading, or to evaluate market prices if public trading of CfD products is introduced in a (new) price area.

We have suggested to use statistical elicitation for weighting together the regression coefficients. Instead, we could have fitted one common model for all price areas, and elicited on each regression coefficient. In our case, the price areas are too different for this to work, but this might be different in other applications. However, the expert would then need to have an opinion on the actual regression coefficients, which we find unrealistic.

NASDAQ OMX Commodities's CfD products are traded for eight horizons (one month ahead to three years ahead). We found that the effect of each covariate is different for each horizon, and that a separate model for each horizon is needed. Generally, there should be common features for neighbouring horizons (Aas and Kåresen, 2004; Benth et al., 2008), especially between those with delivery period of the same length, and some sort of local shrinking could be applied (Hastie et al., 2009).

The other side of the coin is the risk premium problem, which has been given more attention previously, especially for the system price (Botterud

et al., 2010; Marckhoff and Wimschulte, 2009; Lucia and Torro, 2011). If there are no risk premiums,

$$E_{t-k}[SA_{ta}] = FW_t + CfD_{ta},$$

or

$$E_{t-k}[SS_{ta} - SA_{ta}] = CfD_{ta},$$

where  $E_{t-k}$  is the expectation conditioned on all relevant information available at time  $t - k$ . The risk premium can lie in  $FW_t$ ,  $CfD_{ta}$  or both. Our method should work equally well for risk premium estimation. A related problem would be to build similar models for the expected area spot prices,  $E_{t-k}[SA_{ta}]$ , which could also benefit from our approach.

The methods can be refined further, especially by thinking more on the data process. The historical CfD prices are daily (five days a week) closing prices, settled by NASDAQ OMX Commodities's procedure. This means that the liquidity may vary between price areas, and some products (delivery periods) in some areas for some days have not been traded at all (Frestad, 2012). Typically, products with a delivery period far ahead are traded less than other products. Incorporating data on the traded volume as well as the prices, including bid and ask prices, may enhance both the hypothetical CfD prices, as well as our understanding of the CfD products that are supposed to be traded.



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Figure 1: Current Norwegian price areas. Danish price areas DK1 and DK2 correspond to western and eastern Denmark, respectively, while Sweden and Finland each were single price areas during our data period.

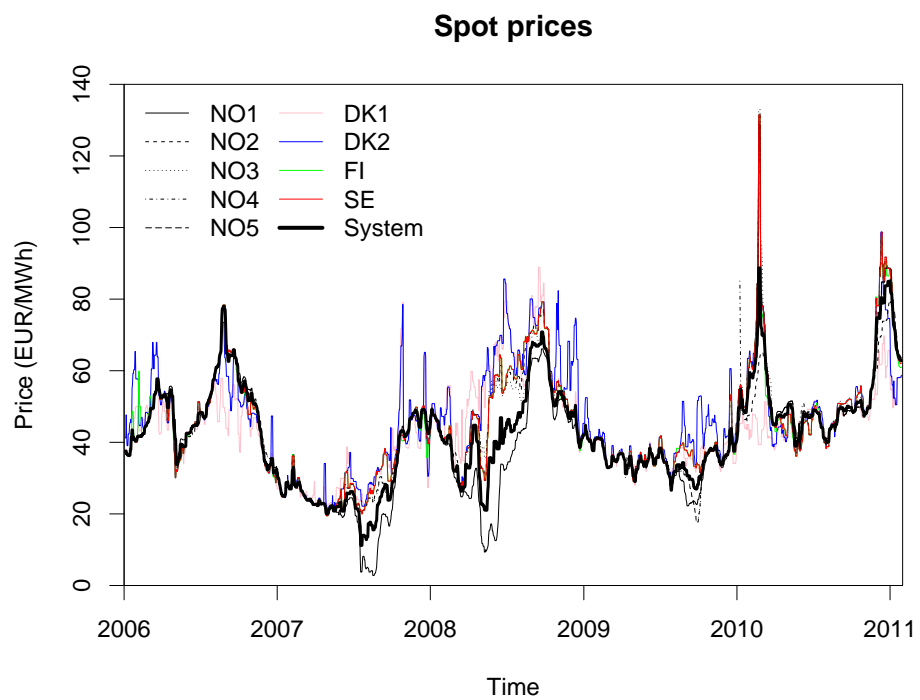


Figure 2: Area spot prices, with system spot price (heavy black curve)

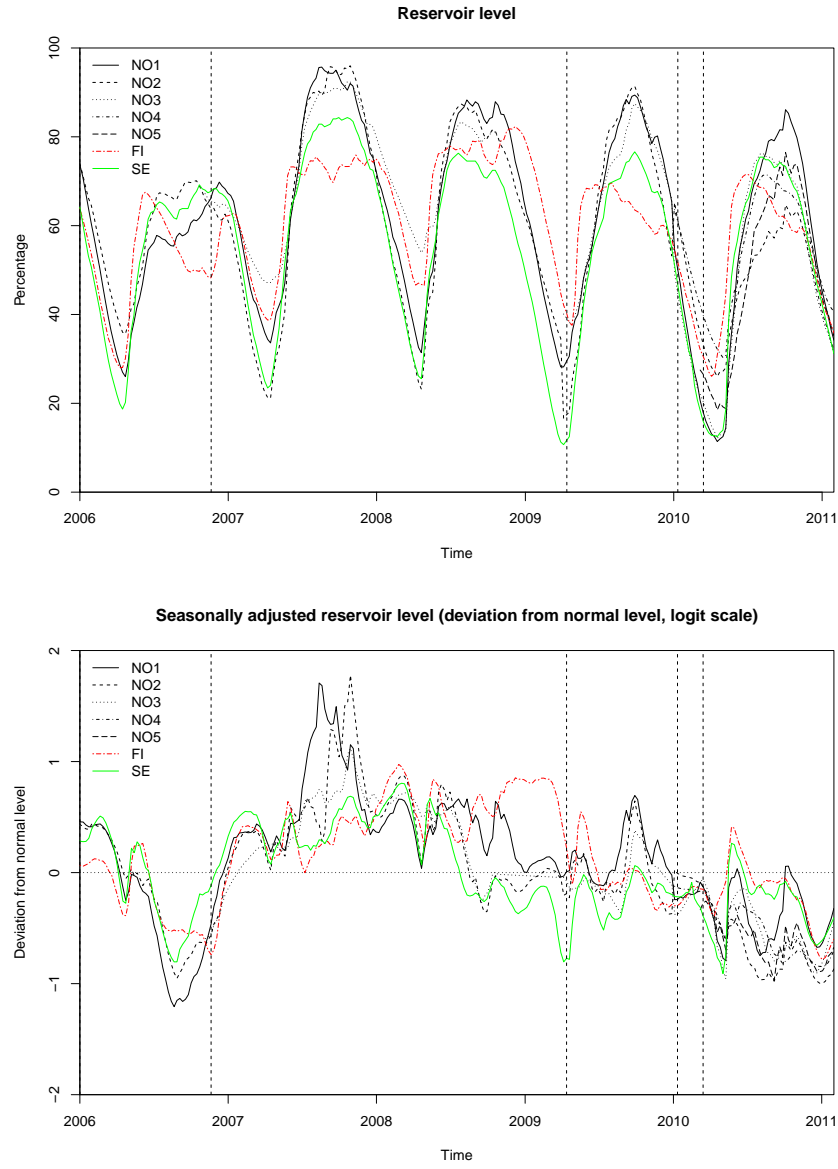


Figure 3: Upper: Water reservoir levels for the different price areas. Lower: Seasonally adjusted water reservoir levels. Dashed vertical lines show dates when area definitions changed.

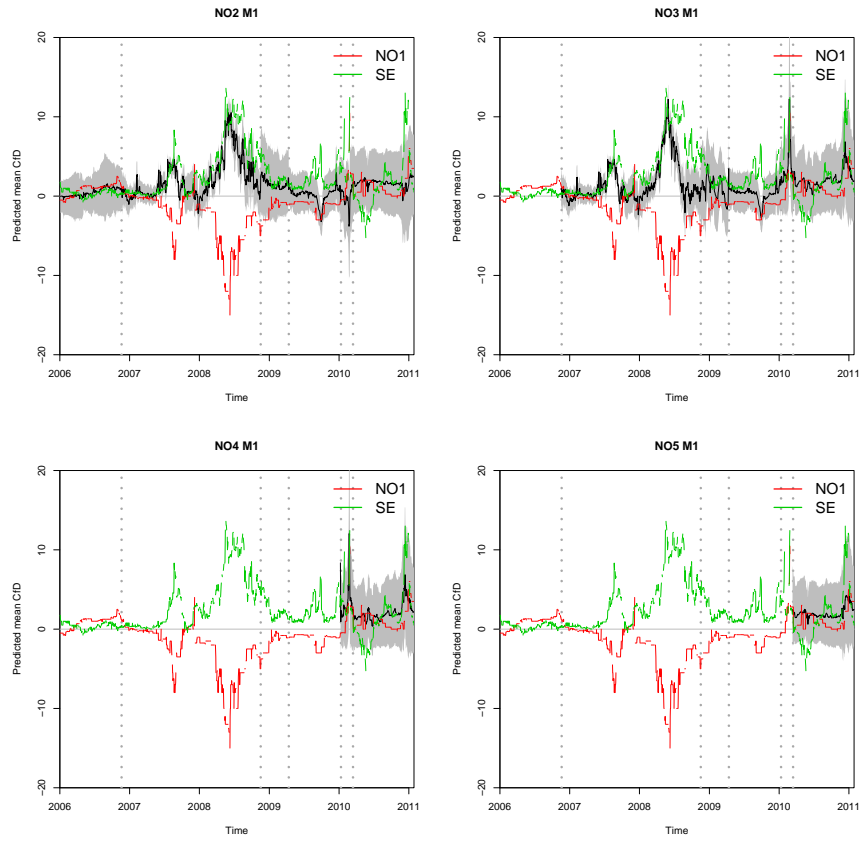


Figure 4: Predicted CfDs for the M1 horizon. A 95% prediction interval is shown in grey. Dashed vertical lines indicate dates when the area definitions changed.



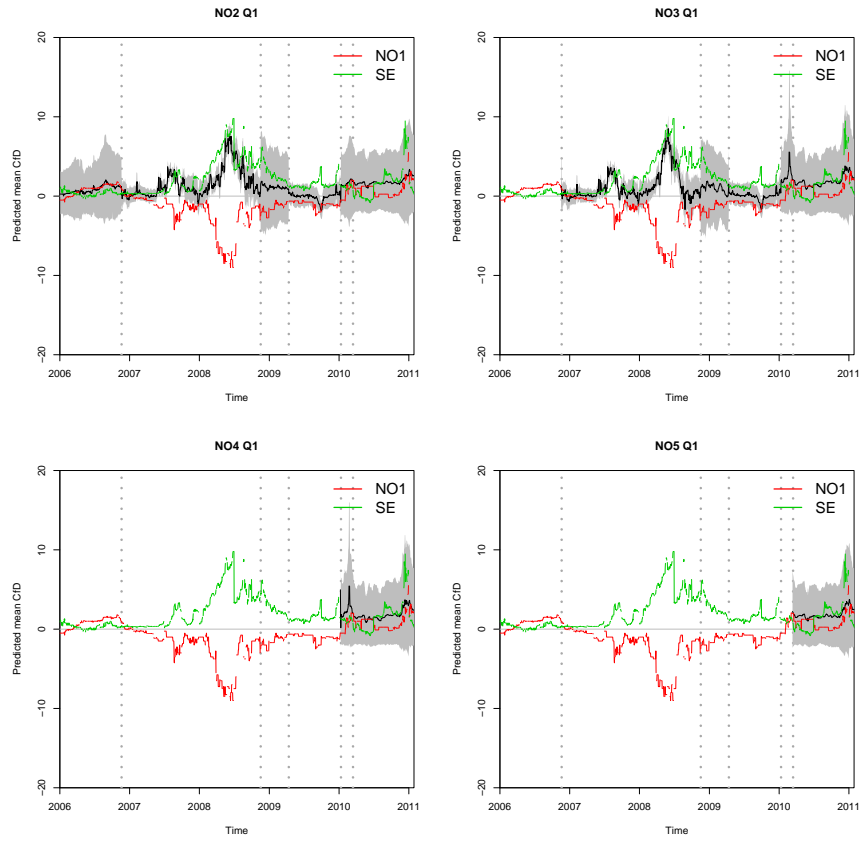


Figure 5: Predicted CfDs for the Q1 horizon. A 95% prediction interval is shown in grey. Dashed vertical lines indicate dates when the area definitions changed.

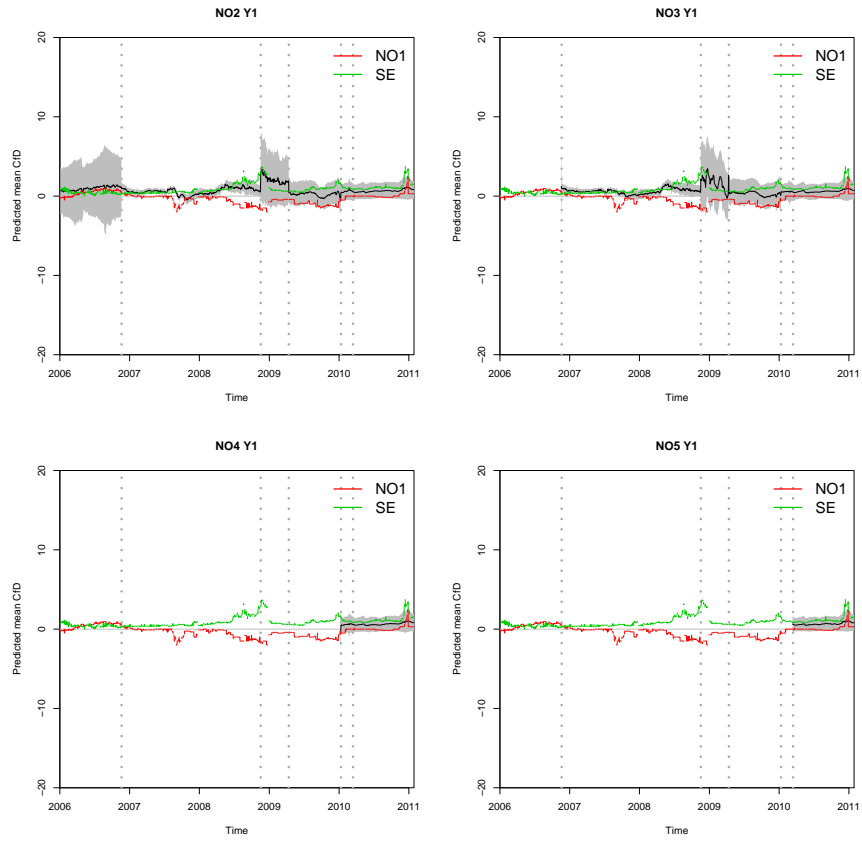


Figure 6: Predicted CfDs for the Q1 horizon. A 95% prediction interval is shown in grey. Dashed vertical lines indicate dates when the area definitions changed.

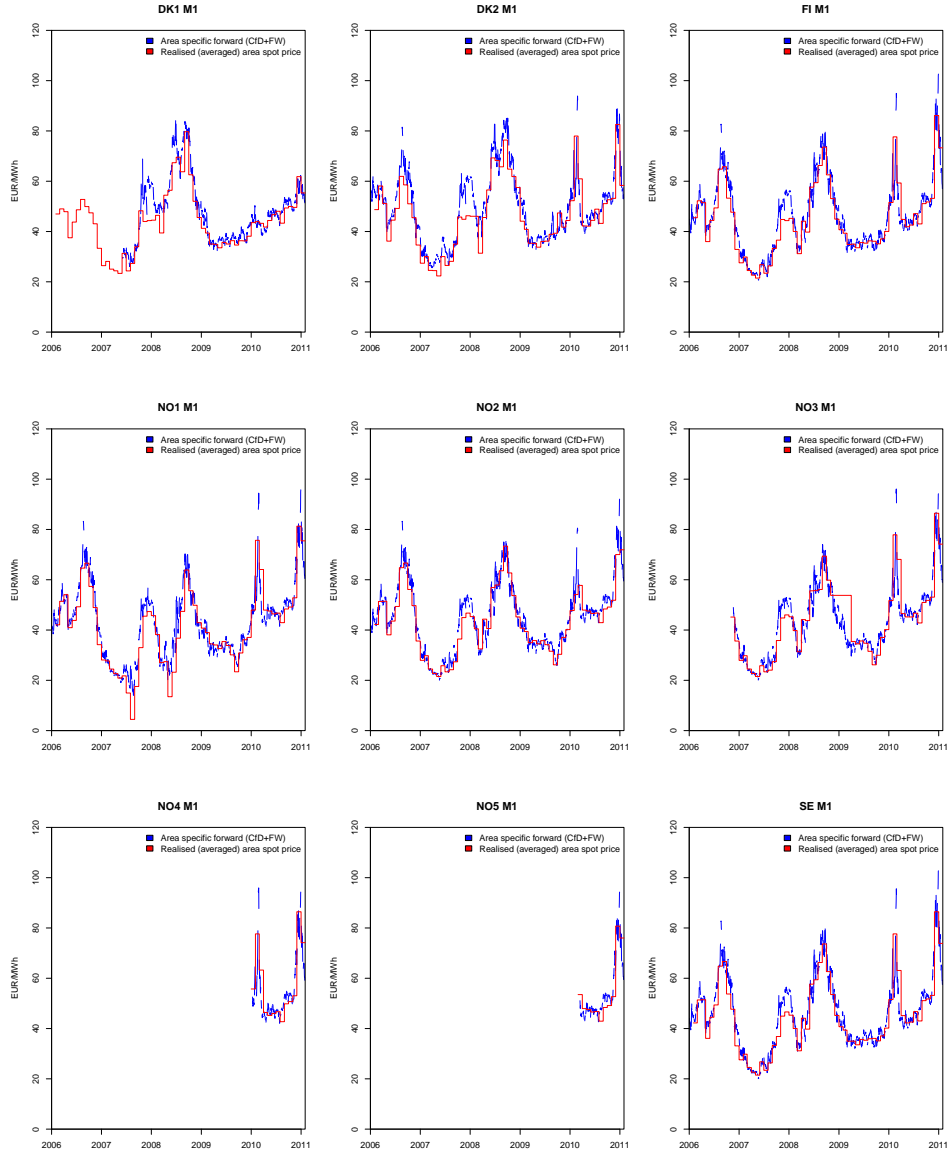


Figure 7: Predicted (NO2–NO5) and observed CfD + FW compared to the realised average area spot price for horizon M1.

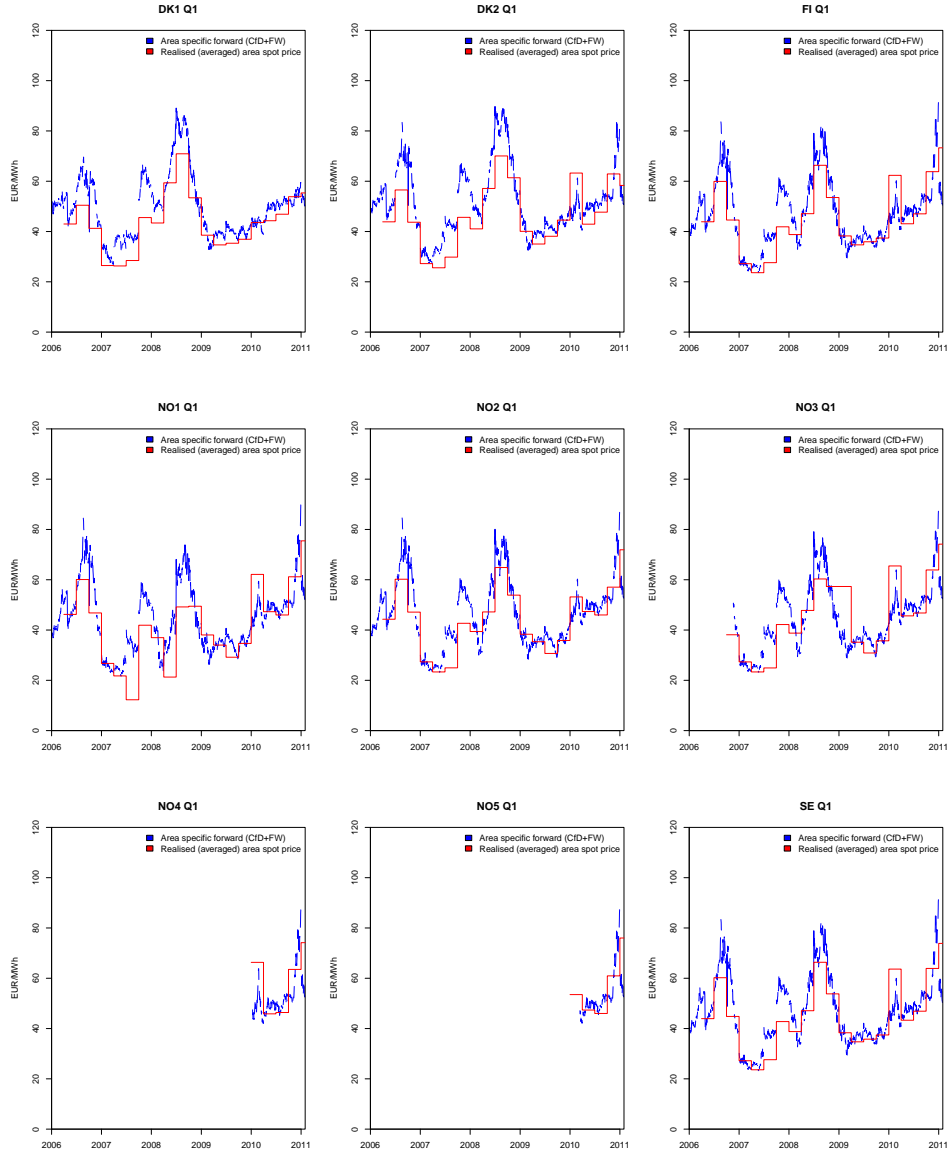


Figure 8: Predicted (NO2–NO5) and observed CfD + FW compared to the realised average area spot price for horizon Q1.

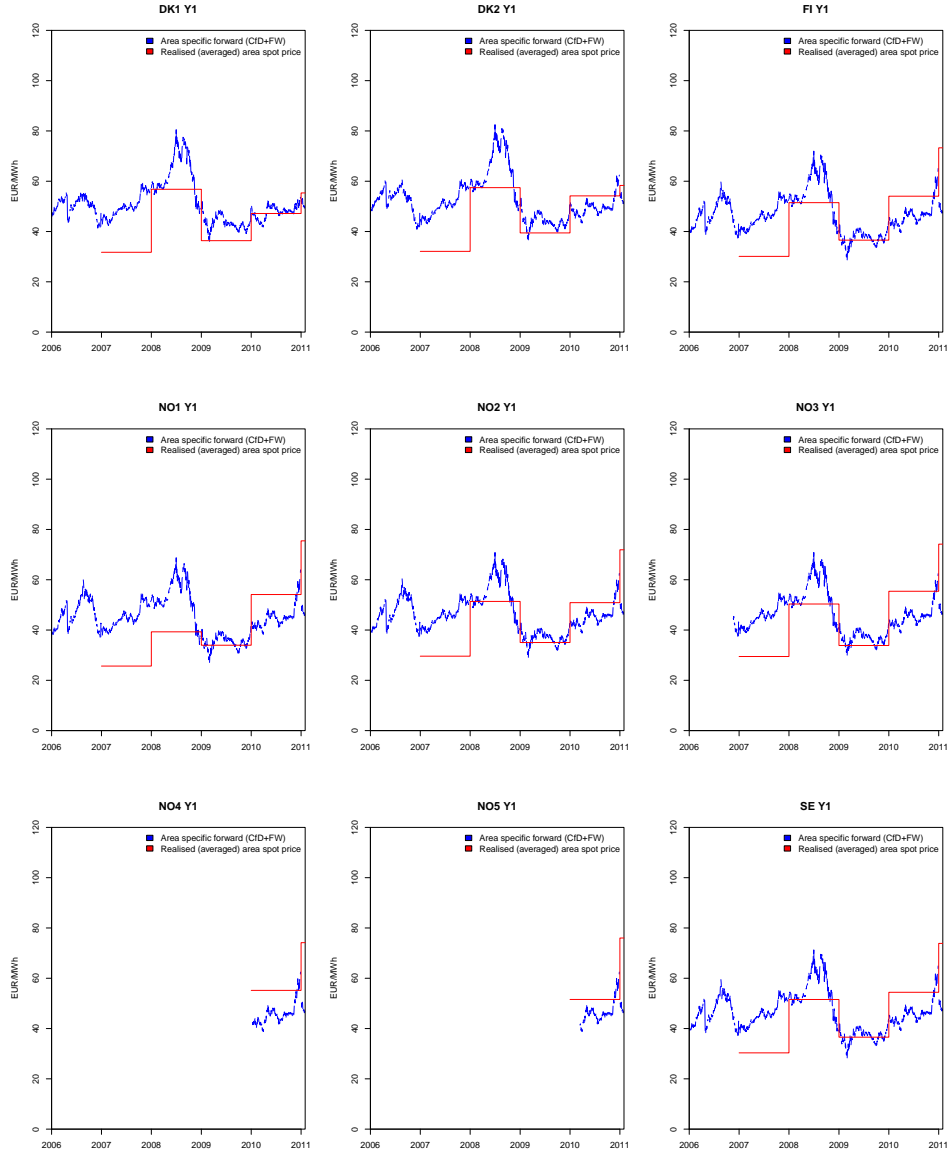


Figure 9: Predicted (NO2–NO5) and observed CfD + FW compared to the realised average area spot price for horizon Y1.